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Detecting Gender Discrimination in Intrahousehold Resource Allocation

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Abstract

The usual methodology for measuring boy-girl discrimination in the intrahousehold resource allocation is the Engel Curve Approach proposed by Deaton (1989). This method is based on the concept of demographic separability in goods, that formalises the idea of certain goods (adult goods) being little or not at all related to some demographic groups (children). The method suggests that, by analysing the consumption on adult goods when a new child is born, it is possible to determine the existence of gender bias. However, in spite of the great popularity of this method, it fails to detect gender discrimination even in societies in which there are huge evidences of its existence. In this paper, I propose to measure gender bias by exploiting the methodological intelligence of the Deaton (1989) procedure, but testing the demographic separability in preferences instead of in goods. To make this concept feasible, I define the system of budget shares as a latent factor model in which the factors represent the underlying motives of the consumption decisions. By testing demographic separability in preferences,the main difficulties faced by the Engel Curve Approach are solved. Finally, this new procedure is illustrated by measuring gender discrimination in the commonly used data from the 1889/90 US Bureau of Labor report, which consists of 1024 budgets of British families. Two consumption drivers are clearly identified: the first one can be associated to basic necessities (e.g food), and the second to luxuries (e.g. alcohol=). In contrast with the results obtained in the literature, a strong evidence of gender discrimination is found.

Keywords: Intrahousehold Resource Allocation,Gender Discrimination, Engel Curves, Factor Models.

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1 Introduction

It is given that measuring boy-girl discrimination in the intrahousehold resource allocation is a desirable objective in itself. If gender discrimination exists within a household, it must be measured correctly and fought against. Apart from that obvious statement, being able to measure how the household wealth is distributed among its members is a topic of great relevance nowadays; see, among many others, Bargain and Donni (2012), Dunbar et al. (2013) and Rodriguez (2016). The reason behind this is the fact that individual wealth not only depends on the total wealth of the household, but also on how that wealth is distributed among its members. Measuring the distribution of resources allocated by parents to their children is particularly relevant because children are the weakest group in the household: they do not belong to it by choice, and they do not have decision-making power or freedom to consume. Additionally, the existence of boy-girl discrimination has been empirically proven in many societies - generally against girls -. Just as an example, Das Gupta (1987), Sen (1990), Klasen (1996), Das Gupta et al. (2003) show a bias against women in terms of mortality and morbidity rates. Sen and Das Gupta (1983) find nutrition discrimination against girls in India; Hazarika (2000) points out that, in South Asia, boys have better access to health services although girls are better nourished, Rose (2000) finds gender bias in time allocation in rural India, Song (2000) finds discrimination against very young girls in China; Gibson and Rozelle (2004) find bias in favour of boys aged 7 to 14 years in Papua New Guinea; Gong et al.(2005) find bias in favour of boys in the expenditure on education in rural China; Kingdon (2005) finds lower educational expenditure to girls than to boys in rural India; Choi and Lee (2006) find gender bias in child immunization in rural areas in India; Kebede (2008) finds gender discrimination against girls in rural Ethiopia; Himaz (2010) finds pro-female bias in rural Sri Lanka in the allocation of education expenditure; Zimmermann (2012) finds evidence of gender bias in favour of girls in education expenditure in India; Azam and Kingdon (2013) find out the existence of pro-male gender bias in the intrahousehold educational expenditure allocation; Barcellos et al. (2014) show that boys receive more investment from parents than girls in rural India. However, most of the studies on gender discrimination focus on external observable factors such as school enrolment, nutrition indicators or mortality rates. This is a consequence of the difficulty of measuring the bias in the allocation of intrahousehold resources that could be explained by three main reasons. Firstly, because of the impossibility of finding two families that have the exact same demographic composition and consumption patterns in real life. Secondly, because expenditure data is usually available at household level instead of at individual level, and thirdly because there are goods that are consumed jointly, and it is therefore difficult to allocate their consumption among the various members of the household.

As a consequence of these data limitations, researchers use an indirect method for measuring boy-girl discrimination in the intrahousehold resource allocation. Such method was proposed by Deaton (1989) and is commonly known as the Engel Curves Approach. For some application of this method in different societies; see, among may others, Haddad and Reardon (1993), Horrel and Oxley (1999), Song (2000), Gibson and Rozelle (2004), Gong et al. (2005) Fuwa et al. (2006), Kebede (2008) and Lee (2008). The Engel Curves Approach is based on the concept of demographic separability that formalizes the notion of certain goods being little or not at all related to some demographic groups. The Engel Curves Approach establishes that boy-girl discrimination can be found by looking at the adult goods, i.e. those goods that are not typically consumed by children. In this way, the addition of a child to the family will cause a negative income effect on the demand for such goods. If the difference in the income effect between both genders is statistically significant, there is gender discrimination in the allocation of resources.

Despite the great popularity and methodological intelligence of the Engel Curves Approach, the results have not been as good as one might have expected. The procedure fails to detect gender bias even when there exits significant boy-girl discrimination at the individual level. In fact, Case and Deaton (2003,11) point out that "it is not clear if there is no discrimination or if, for some reason that is unclear, the method simply does not work."

There are three main difficulties behind the apparent failure of Engel Curves Approach when detecting gender bias. Firstly, the concepts of adult goods and demographic separability are difficult to implement and, as will be explained in the next section, are subject to the arbitrariness of the researcher; see Kebede (2008) and Lee (2008). Secondly, the Engel Curves Approach implicitly assumes that all goods can be categorized as either adult or non-adult. However, this categorization may not be so straightforward in some cases. For example, bellow a certain threshold, food would be associated with the basic need of caloric intake, while, above that threshold, the purpose of such consumption of food could have two different purposes: one associated with nourishment and, therefore, directly related to children, and another one associated with superfluous activities and, thus, subject to be considered as an adult good. Finally, in order to detect boy-girl discrimination, the Engel Curves Approach only considers the income effect derived from the birth of a new child, assuming that there is no substitution effect; see, Deaton (1997).

To solve these problems, a new method for measuring gender discrimination in the intrahousehold resource allocation is proposed. This new procedure measures the effect of an additional child in the consumption associated with adult preferences rather than with the expenditure in adult goods. The idea behind the concept of adult preference goes back to Engel (1857), who pointed out that goods should be categorized according to their ultimate purpose. It is reasonable to think that some purposes and unobservable preferences govern the decisions of household consumption and, therefore, there would be also some preferences demographically separable of children. The objective of this paper is to capture those fundamental preferences by representing the system of budget shares as a latent factor model in which each factor can be interpreted as one of those fundamental forces driving consumption patterns. The latent factors are estimated via Generalized Principal Components, while the factor's loadings and the covariance matrix of the residuals via Maximum Likelihood. Representing the system of budget shares as a factor model allows for the underlying preferences to be expressed as a linear combination of the expenditure in the different goods' categories.

By testing demographic separability in preferences instead of in goods, the main difficulties in the detection of gender discrimination are resolved. First of all, the concept of demographic separability in preferences is easy to implement since it is not subject to the arbitrariness of the researcher because it is completely data driven. Additionally, the consumption in an specific good can be expressed as a linear combination of the factors and, therefore, can be disaggregated into the different motives which explain its consumption. Moreover, the substitution effect is contemplated since, by definition, each latent factor gather those goods that are associated with similar purposes.

Finally, the theoretical results are implemented looking by gender bias in the US Bureau of Labor database composed of 1024 budgets of British families in the textile, coal-mining and metal manufacturing industries collected in 1889/1890. This data set is specially interesting for two main reasons. Firstly, because during this period, the condition of scarcity was prominent and families were forced into making harsh decisions, which is an ideal backdrop for the existence of gender bias. Secondly, because it is the same database used by Horrel and Oxley (1999) who do not find evidences of gender discrimination. I obtain clear evidences of the existence of two factors, being the first one related with the satisfaction of basic necessities, and the other with superfluous consumption. Finally, we find strong evidences of gender discrimination.

The rest of the paper is organized as follows. In section 2, I describe the Engel Curves Approach, the usual methodology for measuring boy-girl discrimination and we show its drawbacks and limitations. In Section 3, I propose a new method for measuring gender bias in the intrahousehold resource allocation which overcome the limitations of the current methodology. In this section, the methodological framework is also explained, as well as the estimation and identification of the underlying factors. Section 4 illustrates both methods trying to find gender discrimination in late Victorian Britain. Finally, Section 5 concludes.

2 The Engel Curves Approach

In this section, the Engel Curves Approach is first introduced and, afterwards, some of the reasons why the procedure could fail to detect gender discrimination in the intrahousehold resource allocation are presented.

The Engel Curves Approach was proposed by Deaton (1989) following the studies of Rothbarth (1943). It is based on the notion of demographic separability of goods, which brings together the idea that that there are groups of goods that their consumption do not have, or have very little, relation with certain demographic groups. In this way, Deaton et al. (1989) also introduce the concept of adult goods, that can be defined as those whose consumption is not related to children (for example, alcohol is usually considered as an adult good).

The intuition behind the Engel Curves Approach is that, if there is no gender discrimination, the birth of a boy or a girl will produce a similar decrease in the consumption of adult goods (income effect). On the contrary, if, for example, there is gender discrimination against girls, the birth of a boy will cause a greater decrease in the consumption of adult goods than in case of a girl.

In order to make the concepts of demographic separability and adult good feasible, Deaton (1989) specifies an Engel curve, which can be estimated from the household survey, that relates the expenditure in each individual good with the total expenditure made by the household, and with other demographic and socio-economic variables. There are various specifications of the Engel curves being the most common the one proposed by Deaton (1989) extending the work of Working (1943) and Leser (1963)[1]:

$$y_g = \alpha_g + \beta_g ln(y/N) + \eta_g lnN + \sum_{1}^{J-1} \gamma_{gj}(n_j/N) + \delta_g z + u_g \tag{1}$$

where y_g represents the expenditure share on some commodity or group of commodities, y is the total expenditure per household, N is the total number of household members, n_j is the number of people in the household in the jth demographic category (girls, boys, women, men), z is a vector of demographic characteristics and dummy variables that allow for possible effects of other household characteristics, such as location, region, nationality or education, and u_g is the error term. The parameters, α_g,β_g,η_g,γ_{gj}, δ_g can be estimated by Ordinary Least Squares (OLS).

Once the Engel curves have been estimated, the most direct way to check the effects of gender in the allocation of resources by the parents, would be to compare the coefficients $\hat{\gamma}_{gj}$ for boys

[1]Some authors suggest that a linear Engel curve may not be appropriate for many commodities. See, for example, Bhalotra and Attfield (1998) and Blundell et al. (1998). One of the possible alternatives to the linear approach could be to use a semiparametric model; see Gong et al. (2005)

and girls using a $t-test$ or an $F-test$. However, Deaton (1989, 1997) proposes an alternative way to measure these effects. Concretely, Deaton (1989) introduces the "Outlay-Equivalent Ratio", defined as the derivative of expenditures on each adult good with respect to an additional child divided by the corresponding derivative with respect to total expenditure.

$$\pi_{gj} = \frac{\partial y_g/\partial n_j}{\partial y_g/\partial y}\frac{N}{y} \tag{2}$$

The ratio shows the relative change in expenditure when a new member of one of the different demographic categories is added to the household, expressed as a ratio of the total household expenditure per person. In other words, *ceteris paribus*, the effect of an additional person of category j to the expenditure in a particular good is given by $\partial y_g/\partial n_j$. The ratio $\partial y_g/\partial n_j$ to $\partial y_g/\partial y$ shows the increase in the total expenses necessary to generate the same additional expense in the good g that is generated by increasing the household with an additional member of category j. For example, if good g is alcohol and n_j is the number of female children in the household, $\pi_{gj} = -0.6$ means that an additional girl in the household has a similar effect on alcohol expenditure as a 60% reduction in the total household expenditure per person. Deaton (1997) explains that the convenience of this expression lies on the fact that if g is an adult good, and if there is no substitution effect, then the "Outlay-Equivalence Ratio" must be identical for all adults goods. We can also see that, if g is an adult good and j is a child, the OER must be negative. In other words, additional children generate a decrease in expenditure in adult goods.

Estimates of the $\pi-$ratios are obtained by replacing the parameters in (1) with their OLS's estimates and y_g and (n_j/N) with their samples means.

$$\pi_{gj} = \frac{\eta_g - \beta_g + \gamma_{gj} - \sum_{i=1}^{J-1}\gamma_{gi}(n_i/N)}{\beta_g + y_g} \tag{3}$$

Once the $\pi-$ratios are calculated, in order to identify the possible list of adult goods, it is necessary to test the null hypothesis that the ratios for each child and adult age are equal across the list of hypothetical adult goods. When a proper group of adult goods is found, the null hypothesis that the ratios for different demographic categories (boys, girls) are equal for the same adult good is tested. Because the $\pi-$ratios for the adult goods will be negative, if the null hypothesis is rejected, the $\pi-$ratio will be significantly lower for one gender than for the other, meaning that, when a child is born, adults decrease the consumption of adult goods differently depending on the gender of the new child. This would mean that there is gender discrimination in the allocation of resources [2].

Deaton (1989) also proposes a simpler alternative procedure to test demographic separability and, similarly, to assess if a group of goods can be considered as adult goods. This procedure also

[2]Full details of the inferential process can be found in Deaton et al. (1989)

relies on the assumption that the expenditure on adult goods depends on the number of children (only through income effect). The procedure regresses the expenditure on each adult good with respects to the expenditure on all adult goods. Using an F-test, the significance of the child's age and gender in the regression can be verified. In such cases in which they are not significant, the goods can be considered as adult goods[3].

Despite the great popularity and methodological intelligence of the Engel Curves Approach, the results have not been as good as expected. Kingdon (2005) shows that the Engel Curves Approach fails to detect gender bias even when there exits significant boy-girl discrimination at the individual level. Moreover, Zimmermann (2012) shows that individual level bias seems to disappear when using the Engel Curves Approach at household level. Even Case and Deaton (2003,11) point out that "it is not clear if there is no discrimination or if, for some reason that is unclear, the method simply does not work". Examples of these failures to detect gender bias using the Engel Curve Approach when there is strong evidence of gender discrimination can be found in Deaton (1989) in Thailand and Côte d 'Ivoire; in Haddad and Reardon (1993) in Burkina Faso; in Subramanian (1994) in India; in Deaton (1997) in Pakistan and Taiwan; in Horrel and Oxley (1999) in late Victorian Britain; in Gong et al. (2005) in China; in Fuwa et al. (2006) in rural India; and in Lee (2008) in rural China, among many others.

There are several reasons behind the apparent failure of the Engel Curves Approach when detecting gender bias.

Firstly, the concepts of adult goods and demographic separability are difficult to implement; see Lee (2008). It should be noted that the detection of adult goods is subject to the arbitrariness of the researcher, since the OERs equality tests are based on a list of possible goods that have been discretionally selected by the researcher. Due to this reason, Kebede (2008) points out that it is necessary to test different combinations of possible adult goods because, even if the original full selection of adult goods is not demographically separable, there may be small groups of goods that are. This could lead the situations where, for the same data set, a certain good can be considered both adult and non-adult, depending on the set of possible adult goods being tested.

Secondly, the Engel Curve Approach implicitly assumed that all goods can be categorized as either adult or non-adult. However, this categorization may not be so straightforward in some cases and, therefore, can make the researchers obtain misleading results. For example, the consumption of food bellow a certain threshold is associated with the basic need of caloric intake, i.e following

[3]However, there is the possibility of spurious correlations and endogeneity of $ln(y/N)$; see, Blundell et al. (1998). To solve this problem, Blundell et al. (1998) and Gong et al. (2005) propose to use augmented factor regression; originally introduced by Holly and Sargan (1982). For its part, Deaton (1989) proposes to use two-stage least squares, and Dunbar et al. (2013) proposes to use the Generalized Method of Moments originally proposed by Hansen (1982).

the Deaton et al. (1989) criteria, food would not be considered as an adult good. However, above that threshold, that is, when the purpose of nourishment has been achieved, the objective of such consumption might be social recognition, recreational activities, etc. In this way, researchers could consider food to be an adult good and, therefore, suitable for measuring gender discrimination. Nevertheless, if considered as an adult good, researchers would be trying to detect gender discrimination in a consumption partially associated with basic needs while, if not considered, they would be failing to include a significant amount of expenditure in the measurement of boy-girl discrimination.

Finally, another reason for the failure in the detection on gender discrimination by the Engel Curves Approach is that the estimation of different individual Engel curves for each good can lead not to include the interaction of goods. That is, in order to identify adult goods, the Engel Curves Approach only measures the income effect, assuming that there is no substitution effect; see, Deaton (1997). This is a very strong constraint, since it assumes an unrealistic human behaviour. For example, a family consumes a high quality wine. However, when a new child is born, they can substitute the wine by beer because it is generally cheaper. If we assume that there is no substitution effect, as the Engel Curves Approach does, we will not be looking for gender discrimination in a significant share of consumption and we will also obtain non-intuitive OERs; for example, increases in the OERs of beer when a new child is born.

3 The Latent Engel Curves. A new approach for measuring gender discrimination

In this section, I propose a new method to detect gender discrimination in the intrahousehold resource allocation, which I will call "Latent Engel Curves Approach". This new method is based on the estimation of the latent forces that govern the consumption behaviour of the households. In this way, instead of basing the detection of gender bias on the demographic separability in goods, which generates the problems explained in the previous section, we will be studying the demographic separability in preferences and, by doing so, measuring gender discrimination more accurately.

The section will be organized as follows: in the first subsection, the intuition behind this new procedure and the reasons why it overcomes the problems of the classical methodology will be explained; in section 3.2, we will represent the system of latent Engel curves as a latent factor model, we will explain its estimation and the identification of the latent forces that represent the consumption patterns of households; finally, we will see how we can use this approach to detect gender discrimination.

3.1 Demographic separability in preferences

Since Engel (1857), researchers have tried to understand the Engel Curves through the latent causes that determine their shape, i.e. the fundamental reasons that explain consumption decisions. In fact, Engel (1857) himself suggests that goods must be classified according to the final purpose they satisfy, and identifies several categories of goods according to their ultimate purpose; "nourishment", "clothing", "recreation" etc. See, Chai and Moneta (2010). Therefore, it could be reasonable to think that, when there are income changes, non-observable purposes and preferences govern the decisions of household consumption. Thus, all the observed Engel curves can be interpreted as a mixture of these basic motives; see, Lewbel (1991) and Barigozzi and Moneta (2016). For example, the analysis of food consumption from this new perspective would lead to the conclusions that it is determined by two fundamental reasons: the satisfaction of a basic need, and a recreational activity.

The objective of this paper is to capture these basic reactions in order to measure gender discrimination in intrahousehold resource allocation by testing demographic separability in preferences instead of in goods. That is, the dependent variable in (1) would now be the latent preferences that govern consumption decisions. Following the nomenclature proposed by Barigozzi and Moneta (2016), this new equation will be called "latent Engel curve"[4]. Additionally, the "Latent Outlay Equivalent Ratio"(LOER) can be defined as the analogue the OER in this new context. Thus, we will have a LOER for each underlying preference instead of one OER for each good. The LOERs can be interpreted as the increase in the total expenses necessary to generate the same additional expense in the fundamental purpose of consumption, f, that is generated by increasing the household with an additional member of category j. Using this new methodology, the goods will be automatically separated the goods according to the final purpose for which they serve and, therefore, following the reasoning of Deaton (1989), if f is a purpose that is not related with children, the LOER will be negative. In this way, once the factors that correspond to adult preferences have been obtained, the equality of the LOERs can be tested for each age and gender group.

By testing demographic separability in preferences instead of in goods, we solve the main problems identified in the Engel Curve Approach. First of all, the possible arbitrariness of the researcher previously explained is eliminated, since the proposed methodology is completely data driven, and automatically groups goods that have a similar purpose.

Additionally, by representing the system of budget shares as a factor model, the consumption of one good can be written as a linear combination of the underlying motives which drive its consumption. Therefore, a proportion of the consumption of a certain good can be associated to an adult preference, and the remaining proportion to a non-adult preference. In this way, we will

[4] For full details of the concept of latent Engel curves see Barigozzi and Moneta (2016).

be overcoming the naive conception that a good is either adult or non-adult good. Moreover, the problem of determining the number of adult goods in which gender discrimination is found in order to affirm that gender bias actually exists is not arbitrary anymore. With the new methodology, if gender discrimination is found in the factor associated with adult preferences, i.e. the factor with negative LOER, it can be asserted.

Finally, the Engel Curve Approach only considers the income effect produced when there is an additional child in the family, assuming that there is no substitution effect. This is a very strong and unrealistic assumption that can produce counter-intuitive and misleading results. When estimating the fundamental purposes that govern consumer behaviour, it is not necessary to assume such a strong restriction, since two goods with a common fundamental purpose (substitutable) are explained by the same latent factor that will be used afterwards to measure gender discrimination.

In the next subsection, the system of budget shares will be represented as a latent factor model in which the factors are the underlying motives which drive consumption decisions. The procedure for estimating and correctly identifying the factors will be also explained.

3.2 A latent factor model for budget shares

In order to make the concept of latent Engel curves feasible, it is possible to represent the system of budget shares as a latent factor model in which the factors can be seen as the fundamental motives that govern consumption patterns; see Barigozzi and Moneta (2016).

Following Bai and Ng (2002), we can consider the following factor model to represent the budget shares:

$$y_h = Pf_h + \varepsilon_h, \quad h = 1, ..., H \tag{4}$$

where $y_h = (y_{1h}, ..., y_{Gh})'$ is the $G \times 1$ vector of the expenditure of a household h in each goods' category; $P = (p_1, ..., p_G)'$ is the $G \times R$ matrix of factor loadings with $p_i = (p_{i1}, ..., p_{iR})$; $f_h = (f_{1h}, ..., f_{Rh})'$ is the $R \times 1$ vector of latent factors; and $\varepsilon_h = (\varepsilon_{1h}, ..., \varepsilon_{Gh})'$ is the $G \times 1$ vector of idiosyncratic noises. R is the number of factors and it is assumed to be known.

Considering G categories of goods and a sample of H households, the model can be expressed in matrix notation as follows:

$$Y = PF^{'} + \varepsilon, \tag{5}$$

where $Y = (y_{\cdot 1}, ..., y_{\cdot H})$ is the $G \times H$ matrix of household expenditure, $F = (f_1', ..., f_H')$ is the $H \times R$ matrix of latent factors; and ε is the $G \times H$ matrix of disturbances. Following Bai (2003), the latent factor model in equation (4) satisfies the following standard assumptions:

A. Factors: $E\|f_h\|^4 \leq M$ and $\frac{1}{H}\sum_{t=1}^{H} f_h f_h' \xrightarrow{p} \Sigma_f$ which is an $R \times R$ positive definite and diagonal matrix.

B. Loadings: $\|p_i\| \leq M$ and $\lim_{G\to\infty} \frac{1}{G} P'P = \Sigma_P$ which is an $R \times R$ positive definite matrix.

C. Idiosyncratic components: For all i and t, $E(\varepsilon_{it}) = 0$, $E|\varepsilon_{it}|^8 \leq M$ and $E(\varepsilon_{it}\epsilon_{js}) = \sigma_{ij,ts}$, $|\sigma_{ij,ts}| \leq \bar{\sigma}_{ij}$ for all (t,s) and $|\sigma_{ij,ts}| \leq \tau_{ts}$ for all (i,j). Furthermore, $\sum_{i=1}^{N} \bar{\sigma}_{ij} \leq M$ for each j, $\sum_{t=1}^{T} \tau_{ts} \leq M$ for each s, and $\frac{1}{NT}\sum_{i,j,t,s=1} |\sigma_{ij,ts}| \leq M$.

Being $M < \infty$ and not depending on H and G. Assumption A implies that the factors are orthogonal, i.e. each factor determines a unique underlying motive for consumption. Assumption B requires the matrix Σ_P to be non-singular. These two assumptions together imply the existence of R factors. Under assumption C, the idiosyncratic errors, ε_{ih}, can be correlated across both dimensions as far as the correlations are not too strong; see, Chamberlain and Rothschild (1983). This in an important assumption because the idiosyncratic components are likely to be correlated, as they capture specific reasons behind their consumptions and not just income. Finally, we assume that $\{F_t\}$ and $\{\varepsilon_{it}\}$ are mutually independent groups[5].

3.2.1 Factor extraction

In this subsection, we propose to estimate the underlying factors through a feasible Generalized Least Squares (GLS) estimation with P and the covariance matrix of the errors, Σ_ϵ, being estimated via Maximum Likelihood.

In the context of latent Engel curves, Kneip (1994) and Barigozzi and Moneta (2016) propose to use Principal Components (PC) in order to estimate the latent factors. PC is among the most popular factor extraction procedures due to its simplicity and low computational burden. The $H \times R$ matrix of extracted factors is given by $\sqrt{H}$ times the eigenvectors corresponding to the R largest eigenvalues of the $H \times H$ matrix $Y'Y$. The matrix of estimated factor loadings, $\hat{P}$, is computed by $\hat{P} = \frac{Y\hat{f}}{H}$. Bai (2003) shows that the consistency of the PC estimator when only one dimension goes to infinity, requires to assume asymptotic orthogonality and homoscedasticity of the idiosyncratic components. Only under large G and H, Bai (2003) establishes consistency in the presence of correlation and heteroscedasticity.

The commonly used data for detecting gender discrimination in intrahousehold resource allocation comes from standard expenditure national surveys. These surveys usually provide a limited amount of expenditure categories and, if they do, there is usually a large number of households whose corresponding expenditure amount is zero or missing[6]. Then, the PC method is not consistent

[5] Further details on Factor Models and its assumptions can be found in Bai (2003).

[6] Zimmermann (2012) shows that the Engel Curves Approach fails especially in small samples, probably due to

in the situations commonly encountered in practice, that is, under fixed G and correlated residuals. In order to overcome this problem, Kneip (1994) and Barigozzi and Moneta (2016) propose to build a large-dimension dataset by pooling different survey's waves. This is a very clever idea when the objective is to estimate the latent Engel curves. Unfortunately, the household surveys commonly used for measuring gender bias are not usually available in different waves and, even, in that case, it would be highly likely that the assumptions needed to pool the different waves correctly would not be satisfied [7]. Moreover, one of the drawbacks of the PC estimator is that it is only efficient if $\Sigma_\epsilon = cI_g$, for a constant $c > 0$ and, since the residuals are likely to be correlated, it will provide a non-efficient estimation of the latent factors. However, to use an efficient estimator is a must for us, since the whole procedure for detecting boy-girl discrimination is based on testing the hypothesis that the Latent Outlay Equivalent Ratios (LOER) are the same for different demographic groups and, thus, the standard errors of the estimators play a major role in the procedure.

Choi (2012) shows that Generalized Principal Component (GPC) estimator has a smaller variance than the on obtained by PC. The efficient estimates can be obtained by solving the generalized least squares objective function

$$\min_{F,P} \operatorname{tr}[(Y - PF^{'})\Sigma_\epsilon^{-1}(Y - PF^{'})^{'}] \tag{6}$$

where Σ_ϵ is the $G \times G$ covariance matrix of the idiosyncratic noises. Choi (2012) shows that the factor estimation is given by $\sqrt{T}$ times the first R eigenvectors of the matrix $Y^{'}\Sigma_\epsilon^{-1}Y$. Of course, in practice, Σ_ϵ is unknown and has to be estimated. In the small samples usually encountered in practice, GPC is hardly consistent because it uses the estimated residuals to compute Σ_ϵ, and they depend on $\hat{f}_h$, which is not a consistent estimator of f_h under fixed G; see, among others, Bai and Wang (2016). For that reason, I propose to estimate Σ_ϵ by applying a Maximum-likelihood-based method, since the use of the estimated residuals is not required to estimate Σ_ϵ. Bai and Liao (2016) consider a consistent ML-based estimation of a non-diagonal Σ_ϵ [8].

The quasi-likelihood function (under non-normality in the disturbances) is

$$L(P, \Sigma_\varepsilon, S_f) = \frac{1}{G}\log|Det(PS_fP' + \Sigma_\varepsilon)| + \frac{1}{G}\operatorname{tr}\left(S_y\left(PS_fP' + \Sigma_\varepsilon\right)^{-1}\right) \tag{7}$$

being $S_f = \sum_{h=1}^{H}\left(f_h - \bar{f}\right)\left(f_h - \bar{f}\right)'$ and $S_y = \sum_{h=1}^{H}\left(y_h - \bar{y}\right)\left(y_h - \bar{y}\right)'$ the sample variance of the latent factors and of the observed data, respectively, and $\bar{f} = \frac{1}{H}\sum_{h=1}^{H} f_h$ and $\bar{y} = \frac{1}{H}\sum_{h=1}^{H} y_h$ their corresponding sample means. The standard restrictions for Maximum Likelihood estimators are assumed. Particularly $S_f = I_r$ and $P^{'}\Sigma_\varepsilon P$ is a diagonal matrix which entries are distinct and arranged in decreasing order; see, Lawley and Maxwell (1971).

problems in the aggregation of the data.

[7] see Barigozzi and Moneta (2016) for full details of the pooling assumptions.

[8] Bai and Li (2012 a,b) analyse ML estimation when Σ_ϵ is a diagonal matrix. Also, Breitung and Tenhofen (2011) propose a two step estimation procedure that allows for correlated errors and that is more efficient than PC.

Numerically minimizing the loss function with respect to Σ_ε is difficult since it implies a concave and convex optimization. In order to approximately solve the optimization problem, Bai and Liao (2016) propose to use a Majorize-minimize Expectation–Maximization algorithm, which firstly approximates the concave component by a linear function of Σ_ε, and thereafter approximates the objective function by a convex function. Defining $(\hat{P}_i, \hat{\Sigma}_{\varepsilon,i})$ as the loadings and the covariance matrix of the errors at iteration i respectively, the algorithm can be computed as follows:

- Step 1: Set $i = 0$. Initialize $\hat{P}_0$ and $\hat{\Sigma}_{\varepsilon,0}$. We use the PC estimator as the initial value; see Bai and Li (2012,b).
- Step 2: At iteration $i+1$, $\hat{\Sigma}_{y,i} = \hat{P}_i \hat{P}_i' + \Sigma_{\varepsilon,0}$, $\hat{P}_{i+1} = AM^{-1}$, where $M = \hat{P}_i' \hat{\Sigma}_{y,i}^{-1} S_y \hat{\Sigma}_{y,i}^{-1} \hat{P}_i + I_r - \hat{P}_i' \hat{\Sigma}_{y,i}^{-1} \hat{P}_i$ and $A = S_y \hat{\Sigma}_{y,i}^{-1} \hat{P}_i$[9]
- Step 3: Also at iteration $i+1$, $\hat{\Sigma}_{\varepsilon,i+1} = \hat{\Sigma}_{\varepsilon,i} - k \left(\hat{\Sigma}_{y,i}^{-1} S_y \hat{\Sigma}_{y,i}^{-1} \right)$ where $k > 0$[10]

The ML estimators of P and Σ_ε are still consistent while $H \to \inf$, even when G is fixed [11]. Once $\hat{P}$ and $\hat{\Sigma}_\varepsilon$ have been obtained, the feasile GLS estimator of the factors is

$$\hat{f}_h = \left(\hat{P}' \hat{\Sigma}_\varepsilon^{-1} \hat{P} \right)^{-1} \hat{P}' \hat{\Sigma}_\varepsilon^{-1} (y_h - \bar{y}) \tag{8}$$

By using Generalized Principal Components (GPC) to estimate the underlying factors, and with P and Σ_ϵ being estimated via Maximum Likelihood, we are consistently estimating the factors even when G is fixed and the residuals are correlated; see, Anderson and Rubin (1956), Lawley and Maxwell (1971) and Anderson (2003).

It would be noted that, the proposed method works well in finite samples in the presence of dependent and heteroscedastic errors. Moreover, it does not need G to be very small to outperform the usual methods; see, Bai and Liao (2016) for all the results of the finite sample performance of the method.

[9] Bai and Liao (2016) proposes to penalize the inclusion of many elements out of the main diagonal of Σ_ε. To do so, they propose to use Lasso, Adaptive-Lasso and SCAD. We do not include the penalty function in the algorithm since, in our context, G is going to be small and therefore is not necesary to assume the sparsity of Σ_ε.

[10] In our empirical studies $k = .1$; see, Bai and Liao (2016) who also fix k as 0.1.

[11] The consistency proof of the joint estimation can be found in Bai and Liao (2016).

3.2.2 Factors Identification

It is well known that the estimated factors and loadings are only estimating the space spanned by the columns of F and P, but they do not necessarily identify the individual columns of the real factors and loadings. Therefore, for a unique identification of the factors and in order to avoid the rotational indeterminacy, it is necessary to impose some identification conditions. Bai and Ng (2013) consider three sets of identification conditions such that, if the underlying F and P that generate the data satisfy them, then the estimation of factors corresponds with F.

- IC1: $\frac{1}{T}F'F = I_r$, $P'P$ is diagonal with distinct entries[12].
- IC2: $\frac{1}{T}F'F = I_r$, the upper $r \times r$ block of P is lower triangular with nonzero diagonal entries.
- IC3: The upper $r \times r$ block of P is given by I_r.

However, these conditions are hardly encountered in practice and, even if it was possible to restrict the model imposing these normalizations in the factors and the loadings, there would not be a straightforward economic interpretation of the factors. Therefore, in order to identify the factors and to make them easier to interpret, I propose to use Independent Component Analysis (ICA); see, Comon (1994) and Barigozzi and Moneta (2016), among others.

ICA minimizes all statistical dependencies between the estimated latent factors so that the rotated factors are unique up to a permutation, a sign and a scaling factor. This identification procedure is specially convenient because it is completely data-driven and does not require the use of microeconomic models of consumption behaviour; see, Barigozzi and Moneta (2016). There are several algorithms to compute ICA. The most popular one is the Joint Approximate Diagonalization of Eigen-matrices (JADE) by Cardoso and Souloumiac (1993). JADE first estimates the factor via the GPC method explained in the previous sections and then determines the final orthogonal transformation maximizing the non-Gaussianity of the extracted factors.

In order to apply ICA, it is necessary to impose two assumptions that are easy to comply with. Firstly, the factors should be mutually independent. This is not a strong assumption since, by construction, the factors are mutually independent; see assumption A of the latent factor model. Moreover, the factors and their corresponding Engel curves reflect the basic needs that drive consumption behaviour and, therefore, they express independent consumption patterns of different nature, reacting in an independent way to income changes. Secondly, the marginal densities of the factors have to be non-Gaussian. This can be tested in the data but, in any case consumption expenditures are usually non-gaussian.

[12] IC1 is usually imposed by the ML estimator in latent factor analysis; see, Anderson and Rubin (1956).

3.3 The Latent Outlay Equivalence Ratio

Once the latent factors are extracted and identified, the Latent Outlay Equivalence Ratio (LOER) can be estimated in the same way as the OERs are estimated in Deaton (1989). The first step is to obtain the latent Engel curves as:

$$f_r = \alpha_r + \beta_r ln(y/N) + \eta_r lnN + \sum_{1}^{J-1} \gamma_{rj}(n_j/N) + \delta_r z + u_r \tag{9}$$

As it mentioned in (1), there can be several specification of the latent Engel curves. I propose to use (9) since it presents three main advantages. First of all, when taking logarithms, the regression function is approximately normal; see, Deaton (1997). Secondly, it is consistent with an utility function; see Deaton and Muellbauer (1980), and Kingdon (2005). Thirdly, it fits well with the data in a wide range of cases; see, Deaton (1997). Moreover, it could be reasonable to think of the non-linearity of the latent Engel curve. However, even using nonlinear relationships, the Engel Curve Approach fails to find evidence of gender discrimination in societies in which other results demonstrate its existence. See, Gong (2005).

Equation (9) can be used to compute the Latent Outlay Equivalence Ratio as follows:

$$\Omega_{rj} = \frac{\eta_r - \beta_r + \gamma_{rj} - \sum_{i=1}^{J-1} \gamma_{gi}(n_i/N)}{\beta_r + f_r} \tag{10}$$

Estimates of the ratios are obtained by replacing the parameters with their Ordinary Least Squares's estimates, and replacing f_r with the values of their sample means. Again, it should pointed out that there are many other possibilities for estimating the parameters in (9).

It should be noted that the main reason for using a linear Latent Engel curve, and for estimating its parameters using OLSs, is to show the difference between the Latent Engel Curve Approach and the Engel Curve Approach only due to the concept of demographic separability, not by the specification or the estimation of the latent Engel curve.

The $\Omega-$s can be interpreted as the increase in the total expenses necessary to generate the same additional expense in the underlying purpose of consumption, f, that is produced by increasing the household with a new member of demographic group j. To understand it better, let us imagine that there are latent motives two $R = 2$ that govern consumption decisions. One can be associated with the consumption of basic needs (food, clothing, etc.), and the other with luxurious consumption (drugs, leisure, etc.). Therefore, if f is the latter factor and n_j is the number of male children in the household, a $\Omega-$ equal to -0.1 means that an additional boy in the household has the same effect on luxurious consumption as a 10% reduction in the total household expenditure per person.

Once the $\Omega-$ratios are calculated, it is also necessary to test the null hypothesis that the ratios for different population categories are equal for the same adult preference.

In order to avoid obtaining the analytical form of the estimation error in (10), we compute the standard errors from a distribution of 5000 fits obtained by estimating and identifying the factors on bootstrapped samples of the observed budget shares. By using bootstrap, it is possible to incorporate both the error derived from the parameter estimation, and the one made when estimating the factors; see, Barigozzi and Moneta (2016).

4 Empirical Application

In this section, both the Engel Curves approach and the Latent Engel Curves approach will be used with the aim of measuring the possible gender discrimination in intrahousehold resource allocation in the 19th-century England. This period is of particular interest in the case of England, since it provides an excellent demographic, economic and social context in terms of gender discrimination for various reasons. In the first place, there is a strong component of male breadwinning and, thus, a vision of masculinity as the basis of economic sustenance, due to the fact that only around 10% of women had remunerated jobs. Additionally, it is a period of prominent scarcity, forcing families into making harsh decisions, which is an ideal backdrop for gender bias allocation. Moreover, historians have found several evidences of gender discrimination: Humphries (1990), Nicholas and Oxley (1993), Horrell and Humphries (1997), and Horrel and Oxley (2016) find gender bias against girls in nutritional intake, reflected in children's heights; Humphries (1991) and McNay et al. (2005) find that women showed higher mortality rates; and Schofield (1973) and Laqueur (1974) find gender bias in terms literacy rates. However, despite the favourable context and the evidences suggesting gender discrimination, no empirical confirmation has been obtained when analysing intrahousehold resource allocation through the Engel Curves approach; see, Horrel and Oxley (1999, 2013).

In order to make results comparable, the same database used by Horrel and Oxley (1999, 2013) will be used. This dataset comes from the US Bureau of Labor database, and is composed of 1024 budgets of British families in the textile, coal-mining and metal manufacturing industries, collected in 1889/1890.

Table 1 shows a descriptive analysis of the data. The differences among the various industries are remarkable: in the textile industry, the relative importance of children and women in terms of family income is much higher than in the coal and metal industries. This leads to the idea of different patterns of gender discrimination for each industry, and provides an excellent opportunity to test the Latent Engel Curves approach in different contexts. It should be noted that Table 1 is almost identical to the one presented by Horrell and Oxley (1999), making both analyses comparable. After having analysed the data, we use the Engel Curve Approach to measure gender bias. In order to do so, it is necessary to clearly identify the adult goods. Horrell and Oxley (1999) propose an arbitrary list of potential adult goods. Whether a potential good is adult or not is decided using an F-test, as explained in section 2. By doing so, Horrel and Oxley (1999) identify seven adult goods: books, amusement, alcohol, furniture and utensils, property insurance, life insurance, and contributions to labour organizations. With the aim of obtaining comparable final results, the same procedure has been replicated, obtaining very similar conclusions, with the exception of two items: tobacco is considered an adult good, while life insurance ceases to be. Table 2 shows the F-test results.

Table 3 shows the "Outlay Equivalent Ratios" for the identified adult goods, differentiating boys and girls between 0 and 5 years old, and between 5 and 14 years old, in the various industries. In accordance with Horrell and Oxley (1999, 2013), there is no significant evidence of gender discrimination, although there seems to be a slight bias against girls among children between 0 and 4 years old within the metal industry's families.

Having obtained similar conclusions than Horrell and Oxley (1999, 2013), the Latent Engel Curves approach is carry to out to compare the results. To do so, and in accordance to the explanation in section 3, the first step is to estimate the number of latent factors, R , i.e. the underlying forces which drive consumption behaviour. There are several possibilities: Catell (1996) introduces a visual procedure based on a plot of the ordered eigenvalues of the covariance matrix of the data; in the context of Dynamic Factor Models, Bai and Ng (2002) propose several estimators of R based on the information criteria developed for model selection. However, these procedures are consistent only when there is a large number of variables, which is not the case in this context, since there are not many expenditure categories. The Eigenvalue Ratio Test criteria introduced by Ahn and Horestein (2013) is proposed, due to its good finite sample performance. Accordingly, $R = 2$ factors are selected, explaining 54% of the total variance, with the first factor accounting for 36%.

The latent factors and their corresponding loadings are estimated using the Generalized Principal Component procedure also explained in section 3. Once estimated, JADE is applied in order to solve their rotational indeterminacy. It should be noted that this procedure can be applied only if the estimated factors are non-Gaussian. Figure 1 shows the quantiles of the two factors with respect to the Gaussian quantiles, clearly showing that they are not Gaussian and, therefore, allowing for the application of JADE.

Figure 2 displays the weights corresponding to the two factors obtained. The first factor is mostly correlated with the consumption of food and kid's clothes, so it can be interpreted as the underlying motive associated with basic necessities. On the other hand, the second factor is mainly correlated with reading, amusement, adult clothes, etc. Therefore, this factor can be interpreted as the underlying motive associated with luxuries and, thus, it is suitable for finding gender discrimination in the consumption associated with it. It is important to stress that the consumption in one good is expressed as the combination both factors, as can be seen in Figure 1. For example, the consumption of meat is mostly related to the underlying motive associated with the satisfaction of basic needs, but it is also partially associated with luxurious consumption.

Table 3 shows the "Latent Outlay Equivalent Ratios" for the two factors[13]. The LOERs for the first factor are positive in all cases, meaning that the consumption of goods with the underlying purpose of satisfying basic needs increases when a new child is born. By contrast, the second factor is associated with luxurious consumption, showing negative LOERs, meaning that when a child is born, the consumption of such superfluous goods is reduced. There are also strong evidences of gender bias against girls of 5 to 14 years old in coal mining, and of 0 to 4 in metal-producing households. For these demographic groups, parents decrease the consumption associated with recreational purposes in a higher degree when the newborn is a boy than when it is a girl. However, in the textile industry, the opposite behavior is observed. These differences among industries can be explained by the fact that the chances of a girl finding a job in the coal or metal industries are lower than in the case of a boy, whereas in the textile industry women have more opportunities than man. This indicates that the gender bias is actually generated in favour of those children who have more opportunities of finding a job in the industry from which the household gets their income.

[13]Since the sample is small, the bagging GLS estimator is used in order to improve/increase stability.

5 Conclusions

Systematic gender discrimination during childhood can lead to poverty traps, as well as to important future inequalities and to an intergenerational transmission of poverty; see, among others, Bhalotra and Rawlings (2011) and Dunbar et al. (2013). Furthermore, Deaton (1989) points out that policies aimed at increasing household salaries may not be directly associated with a greater wellbeing of its members, and particularly of children affected by gender discrimination. Therefore, a correct measurement of gender discrimination in terms of intrahousehold resource allocation can have a positive impact in political decision-making, and can result in the generation of positive externalities such as the economic development of the affected regions; see Duflo (2012).

For those reasons, a new method for measuring gender discrimination in the intrahousehold resource allocation is proposed in this paper. This new procedure seeks to represent the system of household's budget shares as a latent factor model, in which the latent factors can be interpreted as the underlying motives for consumption. Once the factor associated with superfluous consumption is identified, it is possible to measure whether or not the variation in such consumption depends on the gender of an additional child in the household by estimating the "Latent Outlay Equivalent Ratios". If so, there is empirical evidence of gender discrimination. This procedure exploits the concept of demographic separability in preferences, which formalizes the notion that there are consumption purposes that have no or little relationship with children. By doing so, the major difficulties encountered in the procedure for measuring gender discrimination proposed by Deaton (1989) are resolved.

Finally, the proposed methodology is illustrated by measuring gender discrimination in late Victorian Britain. In contrast to the results usually obtained in the literature, a strong evidence of gender discrimination is found.

In future research, the goal is to extend the Latent Engel Curves approach to a non-linear framework, and to apply it for the measurement of gender discrimination in developing countries.

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Table 1: Total household income earning by age range of the male head of the family, and by industry. The distribution of the total income generated by each demographic group is also presented. Finally, the proportion of women and children working in each industry.

	Age of man					
Textiles	All	≤ 30	31-40	41-50	51-60	61+
Total Income	112.82	81.06	101.18	142.43	155.33	99.75
%Man	66%	89%	78%	53%	48%	64%
%Children	26%	0%	16%	41%	42%	26%
%wife	4%	12%	4%	2%	2%	0%
% Lodging	3%	0%	0%	4%	7%	5%
% Other Income	1%	0%	1%	1%	1%	4%
%children working	35.0%	0.6%	22.5%	52.6%	72.2%	50.0%
%wives working	12.3%	22.9%	11.0%	7.4%	8.0%	0.0%
Sample Size	472	109	182	121	50	10
Coal	All	≤ 30	31-40	41-50	51-60	61+
Total Income	102.540	76.810	89.360	124.270	146.630	93.470
%Man	76%	98%	91%	62%	55%	63%
%Children	22%	0%	9%	38%	43%	14%
%wife	0%	1%	0%	0%	0%	0%
% Lodging	1%	0%	0%	0%	1%	23%
% Other Income	0%	1%	0%	0%	0%	0%
%children working	20.6%	0.0%	9.6%	34.2%	44.0%	30.0%
%wives working	0.6%	3.6%	0.0%	0.0%	0.0%	0.0%
Sample Size	166	28	70	44	17	7
Metals	All	≤ 30	31-40	41-50	51-60	61+
Total Income	112.08	85.27	113.03	134.27	120.29	82.37
%Man	83%	96%	90%	72%	71%	67%
%Children	14%	0%	6%	25%	25%	32%
%wife	0%	0%	1%	0%	0%	0%
% Lodging	1%	1%	0%	1%	3%	0%
% Other Income	2%	3%	2%	1%	1%	2%
%children working	19.0%	0.0%	9.5%	31.0%	46.8%	43.7%
%wives working	0.3%	0.0%	0.8%	0.0%	0.0%	0.0%
Sample Size	345	81	125	87	44	8

Table 2: F-test for adult goods

Good	Adults	Children
Meat	11.9**	13.4**
Coffee	7.2**	8.5**
Books	2.5*	0.4
Amusements	7.2**	0.6
Alcohol	2.8*	0.2
Tobacco	3.1*	0.4
Property Ins.	1.6	1.1
Life Ins.	1.1	1.9
Labour org.	2.1	2.2
H's Clothes	11.5**	2.5*
W's Clothes	15.2**	2.4*
Furniture	2.4*	0.9

* F-test significant at 5% level.

** F-test significant at 1% level.

Table 3: Outlay equivalence ratios for adult goods

Gender and Age	Books	Amusements	Alcohol	Property Ins.	Life Ins.	Labour org.	Furniture	All Adult Goods
All households								
boy 0-4	-0.19	-0.2	-0.39	0.28	-0.44	0.15	-0.34	-0.2
girl 0-4	-0.35	-0.25	-0.64	-0.11	-0.21	-0.16	-0.37	-0.28
boy 5-14	-0.31	-0.31	-0.43	-0.39	-0.81	-0.42	-0.89	-0.37
girl 5-14	-0.38	-0.23	-0.56	-0.29	-0.45	-0.21	-0.91	-0.31
man 15-54	-1.02	-0.76	-0.27*	-1.29	-1.16	-1.37	-0.68	-0.69
Textiles								
boy 0-4	-0.43	-0.73	0.41	0.56	-0.59	-0.08	-0.44	-0.04
girl 0-4	-0.49	-0.73	-0.48	-1.09	-0.72	-0.33	-0.84	-0.31
boy 5-14	-0.33	-0.57	-0.18	1.06	-0.86	-0.36	-0.24	-0.19
girl 5-14	-0.38	-0.37	-0.18	-0.73	-0.37	-0.82	-0.47	-0.25
Coal								
boy 0-4	0.05	0.04	-0.026	-	1.89	-0.15	-0.49	-0.05
girl 0-4	0.15	-0.28	-0.459	-	-2.38	0.86	0.14	-0.4
boy 5-14	-0.02*	-0.31	-0.455	-	-3.15	-0.14	-0.57	-0.61
girl 5-14	-0.81*	-0.82	-0.123	-	-1.01	-0.39	-0.90	-0.61
Metals								
boy 0-4	-0.19	-0.11	-0.48	0.66	-1.13*	0.98	-0.99	-0.23
girl 0-4	-0.03	-0.08	-0.27	0.22	0.94*	1.16	-0.28	0.03
boy 5-14	-0.66	-0.43	-0.77	-0.68	-0.47	-0.71	-0.73	-0.49
girl 5-14	-0.47	-0.13	-0.98	-0.22	-0.01	0.43	-0.66	-0.31

* Significant differences in the correspondent demographic group at 5% level.

Table 4: Latent Outlay Equivalence Ratios corresponding to the two latent factors extracted.

Gender and Age	Factor 1	Factor 2
All households		
Boy 0-4	3.23	-3.13
Girl 0-4	3.13	-3.06
Boy 5-14	2.95	-2.8
Girl 5-14	2.69	-2.52
Textiles		
Boy 0-4	1.92	-2.28
Girl 0-4	1.93	-2.97
Boy 5-14	3.1	-2.39
Girl 5-14	2.93	-3.25
Coal		
Boy 0-4	3.89	-2.77
Girl 0-4	4	-2.79
Boy 5-14	2.59	-3.93
Girl 5-14	2.54	-3.19
Metals		
Boy 0-4	2.31	-3.73
Girl 0-4	1.74	-3.01
Boy 5-14	3.21	-2.79
Girl 5-14	2.82	-2.69

* Significant differences at 5% level.

Figure 1: Quantiles of latent factor versus quantiles of standard Gaussian distribution. Top panel: first latent factor; Bottom panel: second latent factor.

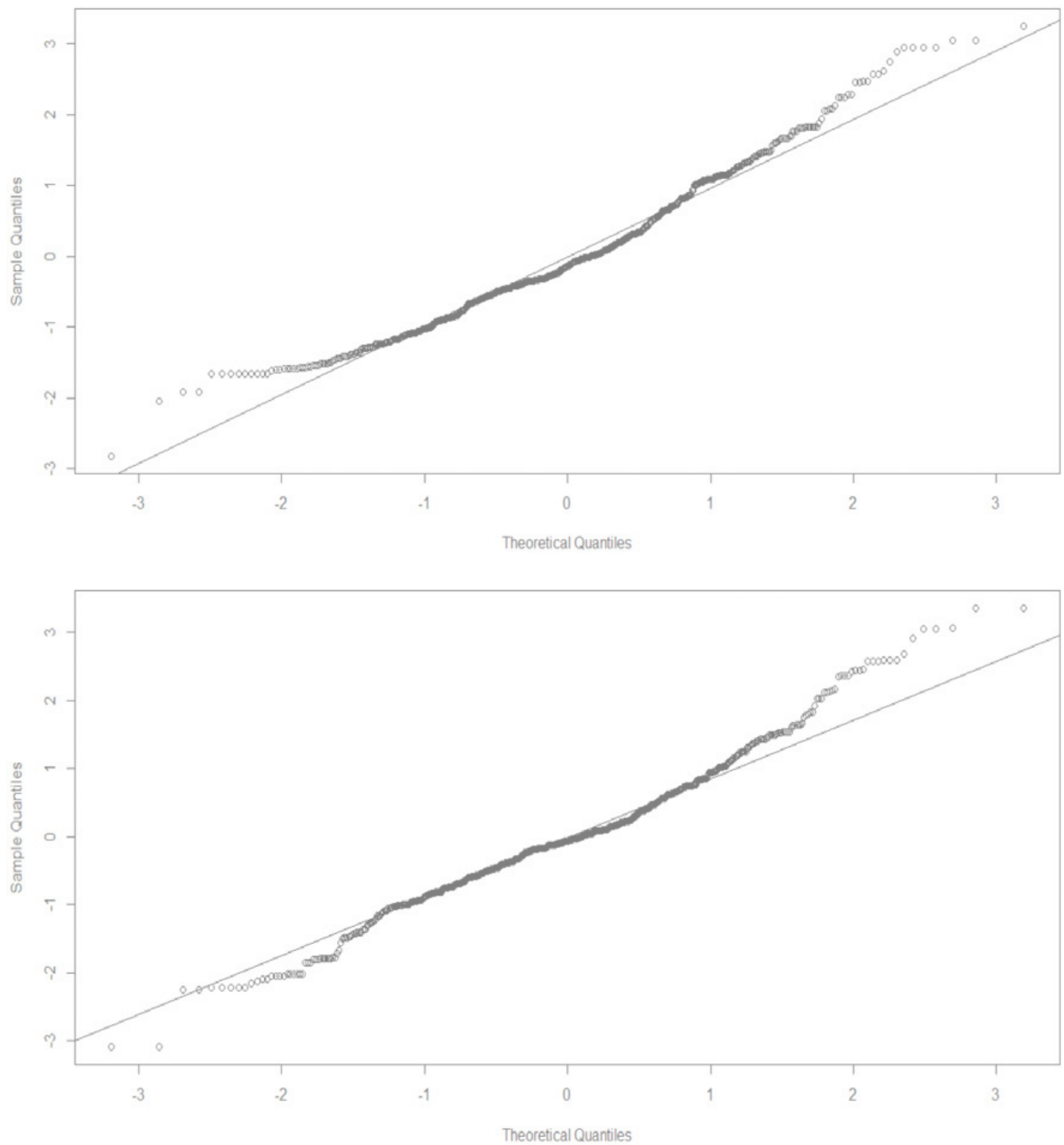

Figure 2: Top panel: First factor weights for each good category. Bottom panel: Second factor weights for each good category.